Unsupervised Contrastive Learning for Acute Respiratory Distress Syndrome Diagnosis

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Introduction

Access to labeled data is a challenge in healthcare data research that often limits the development and deployment of intelligent ML-based predictive analytics in the clinic. The contrastive learning framework is a novel methodology proposed by Chen et al. (SimCLR) that performs model training in a fully unsupervised, architecture-agnostic way. Our objective is to test its utility in predicting Acute Respiratory Distress Syndrome (ARDS) using frontal chest X-ray images.

The prediction of ARDS was chosen as an evaluation for the model due to how ARDS is diagnosed by identifying key visual features such as asymmetrical consolidation with air bronchograms, septal lines, etc. from a patient's frontal chest X-ray scans.

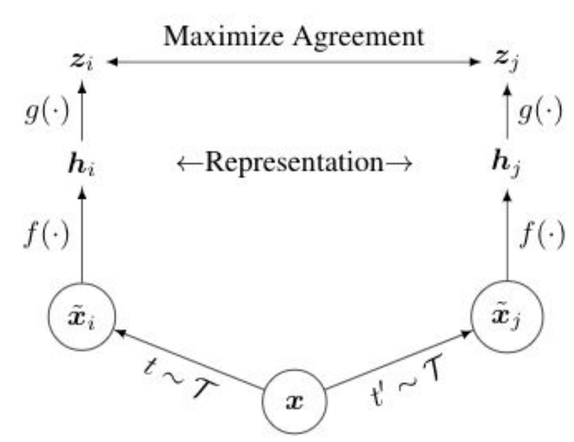


Figure 1. The SimCLR framework uses a contrastive loss in the latent/feature space to maximize agreement of representations under data transformation.

The SimCLR framework uses a contrastive loss function described in Fg. 1 during pre-training, a ResNet-50 backbone as a base encoder network for feature extraction from the chest X-ray images (Fg. 2), a configurable projection head for the classifier layer, and specific data augmentations for pre-training and training dataset.

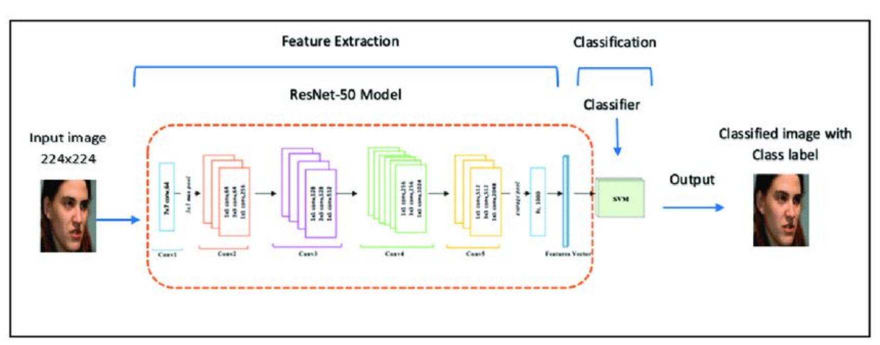


Figure 2. Diagram of the ResNet-50 feature extractor and projection head classifier on a sample image.

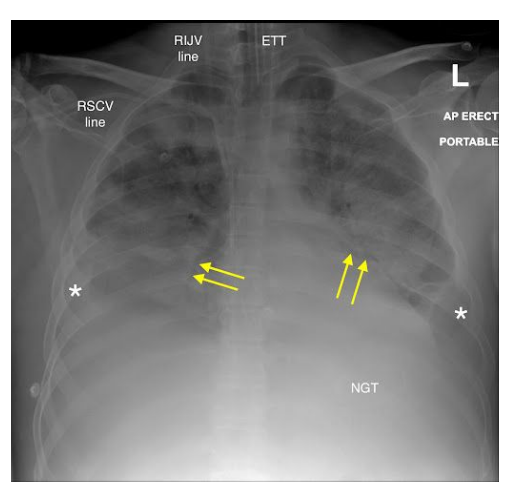


Figure 3. Sample of frontal chest X-ray scan with visual features indicating ARDS.

Methods

- The SimCLR framework (with contrastive loss function, stochastic data augmentation module, ResNet-50 backbone architecture) was used as a baseline for construction of the ARDS-specific ML pipeline.
- Each aspect of the ML pipeline was written in Python, with the ResNet-50 architecture and overall network (base encoder + classifier/projection head) implemented in PyTorch using the torch.nn Module.
  - Later, the main model training/testing code was rewritten in PyTorch Lightning to allow for simple single- & multi-GPU training.
- The model training and testing was performed in Google Colaboratory, a virtual execution environment for running code that offers access to remotely-hosted GPUs via CUDA.
- For an initial experiment with the SimCLR framework, Tony Lin's TensorFlow → PyTorch checkpoint converter was used to convert the weights of the TensorFlow SimCLR model pre-trained on ImageNet into a PyTorch format for testing via linear evaluation.
- The CIFAR-10, CIFAR-100, and Caltech-101 datasets were used during the linear evaluation phase, the NIH ChestX-ray14 dataset was used for pre-training of the ARDS-specific pipeline, and a CHOP dataset of frontal chest x-rays was to be used for testing of the ARDS-specific pipeline.

Schematic of Proposed ARDS-specific ML Pipeline

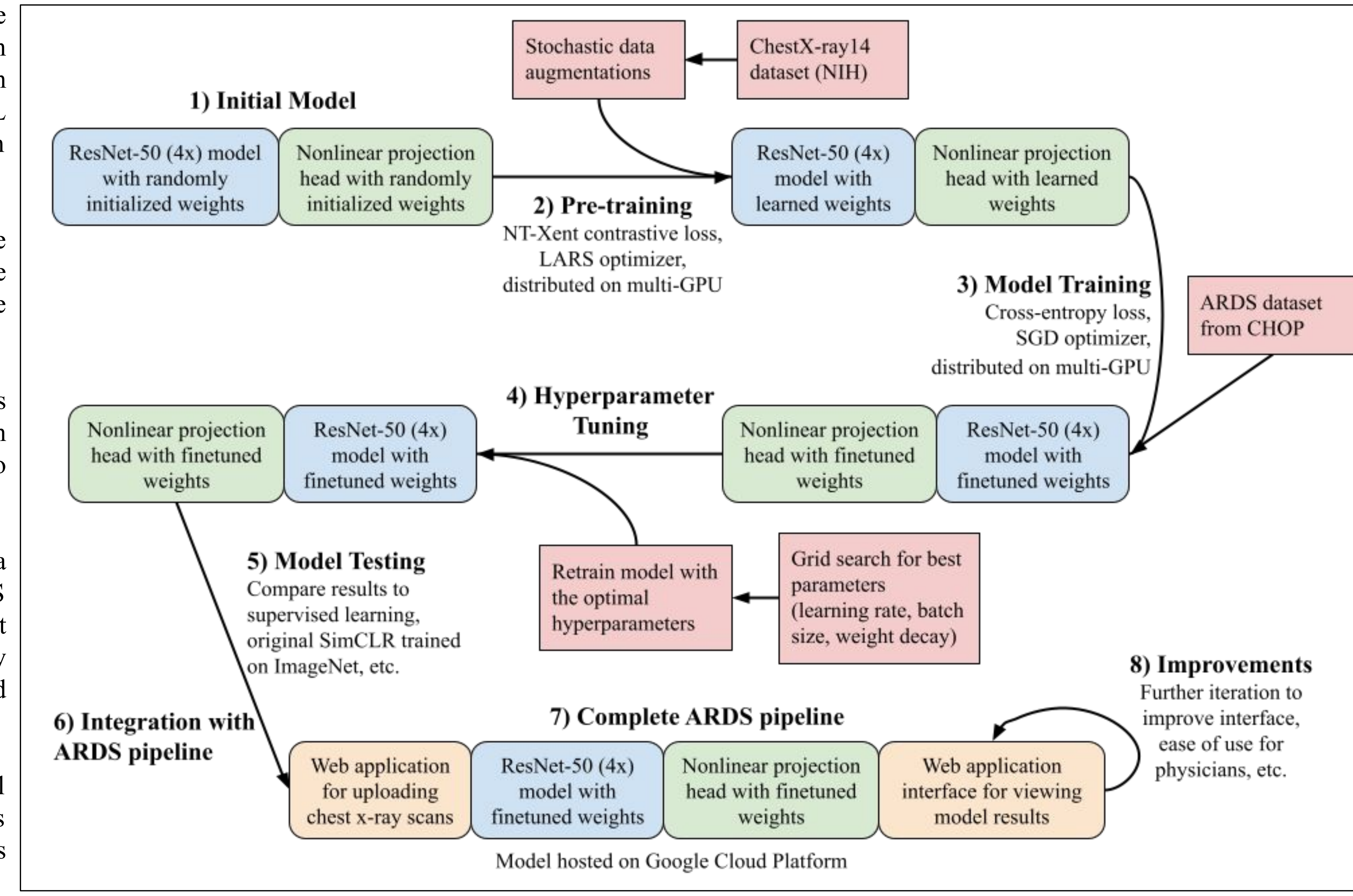
Once we were successfully able to replicate the Chen et al. (SimCLR) linear evaluation results (described in the section below), an ARDS-specific version of the SimCLR ML pipeline was developed using the PyTorch Lightning framework.

The implementation of the pipeline is made up of 8 distinct stages starting from the initial model up until improvements on the pipeline, shown in the diagram to the right.

During pre-training data augmentations such as Random Resized Crop and Random Horizontal Flip with p=0.5 are applied to the ChestX-ray14 dataset.

During model training, no stochastic data augmentations are applied to the ARDS dataset. Instead, SGD (Stochastic Gradient Descent) with a criterion of Cross-Entropy Loss is used to finetune the pre-trained model's weights.

A grid search is done to find optimal hyperparameters, and the pipeline's results are compared to other baselines such as supervised learning.



SimCLR Linear Evaluation & Finetuning

Before designing the ARDS-specific ML pipeline, we attempted to reproduce the results reported by Chen et al. (SimCLR) for 3 datasets, CIFAR-10, CIFAR-100, and Caltech-101. This was done via transfer learning: the weights from ResNet-50 (4x) pre-trained on ImageNet were frozen, the last fully-connected layer was replaced with an L2-regularized logistic regression classifier set to the dataset's # of classes, and only the linear classifier was finetuned on training set.

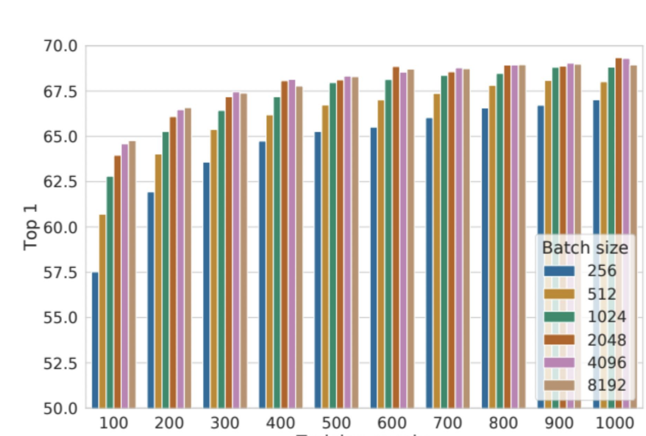


Figure 4. The SimCLR paper's reported results for ResNet-50 linear evaluation models trained with different batch size and epochs.

Dataset	SimCLR reported result	Linear eval result
CIFAR-10	95.3	93.14
CIFAR-100	80.2	78.09
Caltech-101	93.9	91.51

Table 1. Comparison of results reported by Chen et al. (SimCLR) and the test accuracies from transfer learning with ResNet-50 (4x) + linear classifier layer.

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Discussion & Future Directions

- In the future, we plan to complete the model training (with chestX-ray14 dataset) and finetuning phases on Google Cloud Platform or another cloud execution environment, as Google Colab's GPU proved unable to handle the large RAM and compute requirements necessary for training the model.
- We also plan to perform more a detailed comparison of the results obtained from the ARDS pipeline to the supervised learning baseline, the base SimCLR framework pre-trained on ImageNet, and different approaches to contrastive learning such as MoCo (Momentum Contrast).
- As shown in the ARDS pipeline schematic, there are also many different directions to explore after the model has been finetuned & tested, including the creation of a web application interface for physicians to upload chest x-ray scans and view the model's diagnosis.

References

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